FORECAST QUALITY ASSESSMENT OF SEASONAL EXTREME WIND EVENTS

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Summary

In this work, we have assessed the ability of two global seasonal climate prediction systems in forecasting extreme wind speeds at seasonal time scales. Seasonal extremes are defined as three month average of monthly extreme events outside either the 90th or 10th percentiles of 6-hourly 10m wind speed distribution for each ensemble member within a given month separately. We have used retrospective forecasts from the ECMWF seasonal forecast system 4 (ECMWF-S4) and Météo-France's Systems 4 (METFR-S4) during the period 1991-2012. We have focused on November and May start dates and we have calculated averages across each target season for the 0-4 month lead time in all the hindcast period. The performance of the seasonal climate prediction systems in predicting wind speed extremes at different forecast horizons has been evaluated, using the temporal correlation coefficient (TCC) and the Fair Ranked Propability Skill Score (FRPSS). Generally, the extreme forecast skill of ECMWF-S4 is significantly superior to METFR-S4.The seasonal extreme wind events in Q90 threshold tend to show much better performance than those of Q10 thresholds. This indicates that the higher wind speed values are more predictable than those for the lower wind speed values.

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1. Introduction

Extreme weather and climate events, such as extreme cold and heat waves, wildfires, lightning, drought, flooding, downpours, hail, or extreme wind such as local storms and hurricanes, can have profound impacts on human society and cause tremendous economic losses (Karl & Easterling 1999, Easterling et al. 2000a, b, Kunz et al. 2010, IPCC 2012, U.S. Department of Energy 2013).

A number of studies (Peterson 2000, Gresham et al. 1991, Hogan et al. 1999, Ulbrich et al. 2001, Marchigiani et al. 2013, Pascual et al. 2013) have reported that severe extreme wind and related destructive wind storms are responsible for physical destruction, loss of life and property, and economic loss, constituting more than 50% of all total weather/climate related damage and more than 40% of total natural disaster-related destruction. For this reason, a more accurate assessment of the distribution and the probability of occurrence of extreme and severe wind speeds is a necessary condition to improve forecasts that might lead to better protection against such climate risks. This is also a fundamental prerequisite for reducing the uncertainty in the future variability of energy supply and/or demand in the wind energy sector.

Recently, many researchers have investigated extreme wind speeds for a variety of scopes. Kunz et al. (2010), for example, estimated frequency and intensity of extreme wind speeds associated with severe mid-latitude winter storms in regional climate models. The relationships between extreme wind speeds and large-scale atmospheric fields from a statistical downscaling model were studied by Pascual et al. (2013). Under climate change scenarios, Pryor & Barthelmie (2013) have assessed the potential vulnerabilities of the wind energy industry caused by the extreme wind events, and Kumar et al. (2015) also evaluated the performance of CMIP5 suite of climate models in simulating extreme wind speeds. However, little research has been performed on the evaluation of prediction performance for extreme wind speeds at the seasonal time scale. The current study is focused on the seasonal predictions of extreme wind speeds to provide information useful for energy network management.

The main objective of this study is the evaluation of the ability of the seasonal climate prediction systems in forecasting extreme wind speed to minimize the risk of unexpected energy network unbalance. This is achieved through a variety of both deterministic and probabilistic verification measures. More specifically, in this work we investigate the forecast quality of the European Centre for Medium-Range Weather Forecasts (ECMWF) seasonal forecast system 4 (ECMWF-S4; Molteni et al. 2011) and Météo-France's System 4 (METFR-S4; Voldoire et al. 2013) in forecasting the extreme events of 6-hourly 10m wind speed over the period 1991-2012.

In section 2 we discuss the observational and seasonal forecast datasets, and also briefly present the methods used to assess the forecast ability to predict extreme events. The seasonal forecast assessment of extremes is described in section 3. Finally, conclusions are drawn in section 4.

2. Data and methodology

2.1. Forecast systems and observation datasets

We have employed two seasonal forecast systems: ECMWF-S4 (Molteni et al. 2011) and METFR-S4 (Voldoire et al. 2013). The ability of these prediction systems in forecasting extreme events has been explored over the period 1991-2012. In this study, the systems were selected taking into account the availability of 6 hourly 10m wind speed and 2m temperature within the target 3-month seasons at 0-4 months lead time. Each seasonal forecast system has retrospective forecasts integrating 7-months with the first day of May and November as start dates. These prediction systems are briefly described in **Error! Reference source not found.**.

Table 1. *Description of the seasonal forecast systems used in the study.*

Prediction system	AGCM[a]	Resolution	OGCM[b]	Resolution	Ensemble Member
ECMWF-S4	IFS CY36R4	TL255L91	NEMO 3.0	1°lat x1°lon L42	51
METFR-S4	ARPEGE 5.2	TL127L31	NEMO 3.2	1°lat x 1°lon L42	15

The ECMWF-S4 consists of the ECMWF Integrated Forecast Model (IFS) and Nucleus for European Modelling of the Ocean (NEMO) as atmospheric and oceanic components, respectively. The forecast system has 51 ensemble members and its standard forecast, which expands up to 7 month into the future, is initialized on the 1st day of every month from 1981. Details for the ECMWF-S4 can be found in Molteni et al. (2011). The METFR-S4 has been running operationally since September 2012. It consists in a 15 ensemble member hindcasts (0-6 month lead) starting once per month over 1991-2012, based on ARPEGE-Climat version 5.2 coupled with NEMO3.2 as ocean model.

Forecasts from the ECMWF-S4 and METFR-S4 datasets are validated utilizing the ERA-Interim reanalysis (Dee et al. 2011) dataset. ERA-Interim is ECMWF's most recent atmospheric reanalysis, covering the modern satellite era from January 1979 to the present at a spatial resolution of 80 km (T255). ERA-Interim is based on a 2006 version of the ECMWF Integrated Forecast Model (IFS) and uses a four-dimensional variation analysis (4D-Var) for data assimilation.

2.2. Methodology

There are many ways in which extreme climate events can be defined. According to the Intergovernmental Panel on Climate Change (IPCC 2012), a climate extreme is defined as the occurrence of a value of a climate variable above (or below) a threshold value near the upper (or lower) ends (tails) of the range of observed values of the variable. Easterling et al.

[a] AGCM: Atmospheric Global Circulation Model
[b] OGCM: Oceanic Global Circulation Model

(2000a) mentioned that climate extremes could be defined as large areas experiencing unusual climate values over longer periods of time (e.g., large areas experiencing severe drought). Extreme events can also be defined by the impact an event has on society (Easterling et al. 2000a).

For the purposes of this study, we have defined a climate extreme as any value below (above) the 10th (90th) percentile of the chosen variable for a given month. The extreme values based on the percentile thresholds calculated from this process can be considered, for example, as indicators of how much weaker (or stronger) the weakest (strongest) wind days in that month were compared to an average month (Pepler et al. 2015). It is worth to consider that there are many other ways of defining an extreme, and the definition may affect the outcome of the analysis (Becker et al. 2013, Sheridan & Dolney 2003, Nicholls 1995, Easterling et al. 2000b).

In this study, we first measured wind extreme values exceeding the 90th percentile (Q90) threshold (and below the 10th percentile, Q10) of the 6-hourly 10m wind speed output for each ensemble member obtained from the climate prediction systems separately for each month. Afterwards, we computed the seasonal averages for every 0-4 month lead time (e.g., for the 1st November start date, seasonal averages November to January (NDJ), December to February (DJF), and so on until March-to-May (MAM)). Finally, we assess the quality of the two individual climate prediction systems when forecasting the seasonal mean of the monthly wind speed extremes over the common period (1991-2012) between the two prediction systems.

To quantify the performance of the 10m wind speed extreme forecasts, two types of verification measures were applied: the temporal correlation coefficient (TCC) and the fair ranked probability skill score (FRPSS) (Jolliffe & Stephenson 2003, Wilks 2006). Both of them were estimated over the retrospective forecast period of 1991-2012. The TCC is a deterministic measure that is widely used. To measure the TCC, the forecast and observed values are firstly converted to anomalies by subtracting the corresponding climatological average over the period 1991-2012. The TCC is designed to measure the strength of the linear relationship between the departures from the climatological mean field for forecasts and their corresponding observations. The correlation of 1 or -1 implies a perfect linear association between the forecast and observations, whereas a correlation of zero signifies that there is no linear association between the variables. The statistical significance of the TCCs is computed using a Student's two-tailed t-test, being the regions with significant correlation at the 90% confidence level. Figure 1 shows a schematic workflow diagram with the main steps followed.

The ranked probability skill score (RPSS) is employed to evaluate the probabilistic forecasts of multiple categories (Epstein 1969, Murphy 1971, Daan 1985). It measures the cumulative squared error between the categorical forecast probabilities and the observed categorical probabilities relative to a reference (Wilks 2006, Weigel et al. 2007, Acharya et al. 2014). The RPSS, cumulatively calculated for all categories, is analogous to the Brier Skill Score (BSS, Jolliffe & Stephenson 2003, Wilks 2006), except that it is calculated for each category

independently. It is important to note that here the FRPSS has been used instead of the traditional RPSS to make a fair evaluation of prediction systems with different properties, making it possible for forecast systems with a different number of ensemble members to be compared (Ferro 2007 and Ferro et al. 2008). When the value FRPSS equals to 1, it implies that the observed category is always predicted with 100% confidence. FRPSS = 0 implies that the prediction skill is the same as the climatological prediction. Finally, a score <0 means that the forecast system performs worse than climatology. The statistical significance of the FRPSS is calculated using a one-tailed Z-test at the 95% confidence level.

We show the verification measures over land only due to the place which wind farms are mainly installed, but to include points where offshore wind farms might be installed, sea points with a depth equal or less than 50m are also included. Even though all the analyses presented are performed for two variables, in this report we focus on those results obtained for 10m wind speed. For verification results of temperature, refer to the catalog web site (www.bsc.es/ESS/catalogue).

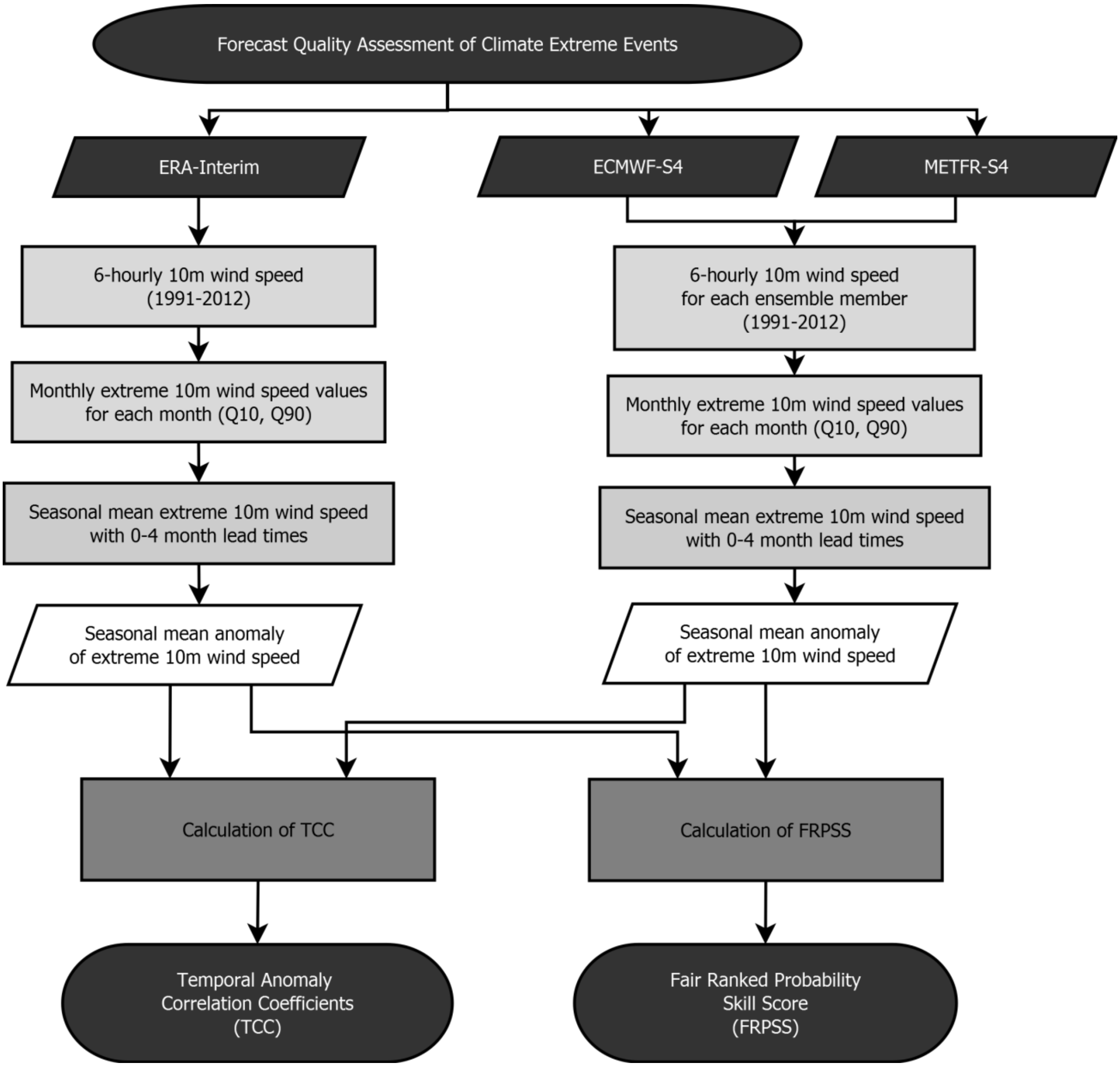

***Figure 1**. Flow chart for the forecast quality assessment of seasonal extreme wind events*

Flow chart on the sequence of the steps in the forecast quality assessment of 10m wind speed seasonal extreme events over the period 1991-2012. The same procedure is also used on the forecast quality assessment of 2m temperature seasonal extreme events.

3. Results

3.1. Forecast skill assessment for extreme climate events

We first evaluate the TCC in forecasting the 3-month seasonal mean, specifically winter (DJF, in Figure 2) and summer (JJA, in Figure 3), of extreme events for the Q10 and Q90 threshold of 10m wind speed measured for each month with 7-month lead time (for both ECMWF-S4 and METFR-S4). In Figure 4 and Figure 5, the verification of the probabilistic seasonal predictions of tercile events defined for the Q10 and Q90 wind extremes is done in terms of FRPSS for each prediction system and for the two seasons (DJF and JJA, respectively).

3.1.1. Temporal Correlation Coefficients

The TCC for the Q10 and Q90 seasonal wind speed extreme events for winter is illustrated in the left and right columns of Figure 2, respectively. Results show that the TCC values obtained for predictions produced by the ECMWF S4 of the Q90 in Figure 2b are significantly superior to those of the Q10 in Figure 2a over the United States, northern China, northern Europe, eastern Africa and the Arabian Peninsula.

The correlation coefficients of Q10 of the extreme wind speeds in the METFR-S4 of Figure 2c indicate a positively significant performance over northern South America, some parts of eastern Africa and the maritime continent (Indonesia). The positively high correlations of the extreme Q90 wind forecast of METFR-S4 are shown in Mexico, northern and central South America, western and eastern Russia, and some parts of the maritime continent (Figure 2d). This extreme wind speed of Q90 for winter also shows statistically significant negative correlation skill in the vicinity of northern Africa.

The results obtained for ECMWF-S4 in the boreal summer (Figure 3) show a significant TCC of extreme wind speed of the Q10 (Figure 3a) and Q90 (Figure 3b) which is very similar for both percentiles. Interstingly, as compared to winter, the distribution of the positive significant skill of the ECMWF-S4 for extreme wind events of summer tends to concentrate along the tropical areas such as the maritime continent (Indonesia), the Indian subcontinent, and northern South America.

Results obtained with METFR-S4 (Figure 3c) show positive high performance of Q10 over northern South America, the Indian subcontinent and the maritime continent. The significant temporal correlation of the Q90 extreme wind forecast (Figure 3d) has similar pattern as that of the Q10 extreme wind event of Figure 3c, excluding the Indian subcontinent and northeastern Australia. This illustrates that both extreme indices (higher and lower wind speeds) show very similar predictability.

In general, the prediction skill for Q10 and Q90 wind speeds of the ECMWF-S4 in Figure 2 and Figure 3 are significantly superior to those of METFR-S4 over the whole global region. However, in a few regions such as middle Europe, western and eastern Russia (in Q90 for DJF), and some parts of the central Asia (in Q90 for JJA), we can find also good skill from the

METFR-S4 climate prediction system. Moreover, the seasonal extreme wind speeds of the Q10 and Q90 during winter season over the extra-tropics indicate slightly better performance than during summer. Common areas showing significantly high extreme prediction skill for both seasons are confined to the maritime continent, eastern Africa and northern South America.

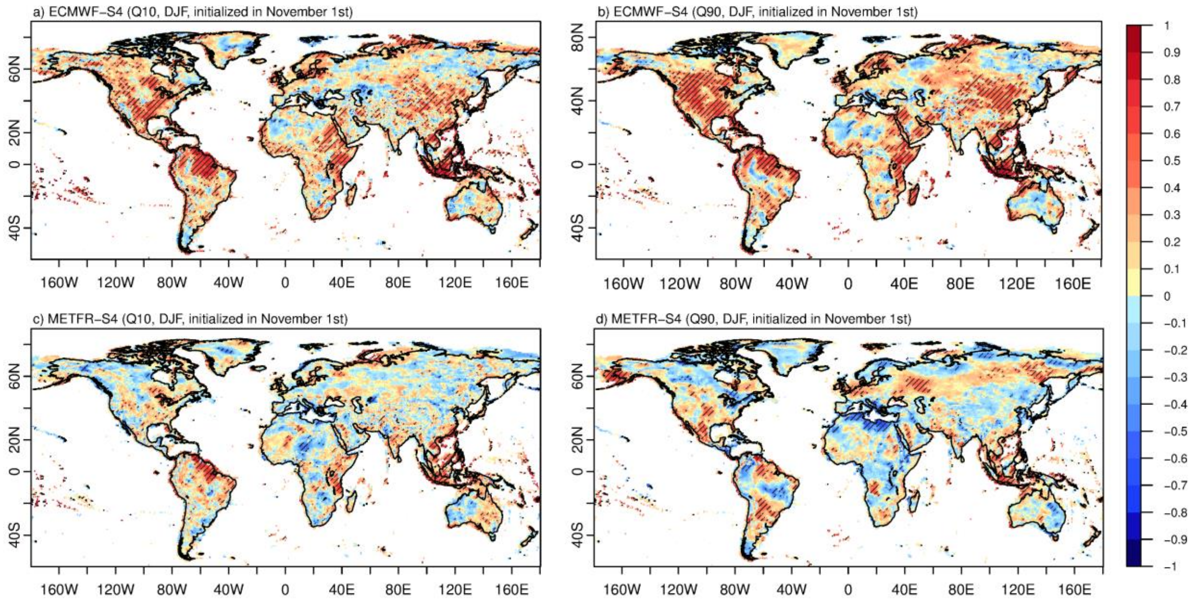

Figure 2. *Temporal correlation coefficients for extreme 10m wind speed*

TCCs between the observed (ERA-Interim) and predicted (ECMWF-S4 and METFR-S4) extreme 10m wind speed over the globe during winter (DJF as the 3-month-average at 1-month lead initialized in November 1st) over the period 1991-2012. Left and right columns are TCC of extreme values for the 10th (Q10, a and c) and 90th percentile (Q90, b and d) threshold calculated from the 6-hourly 10m wind speed within a given month. The hatched areas depict the regions where the correlation is significant at the 90% confidence level from a two-tailed Student's t-test.

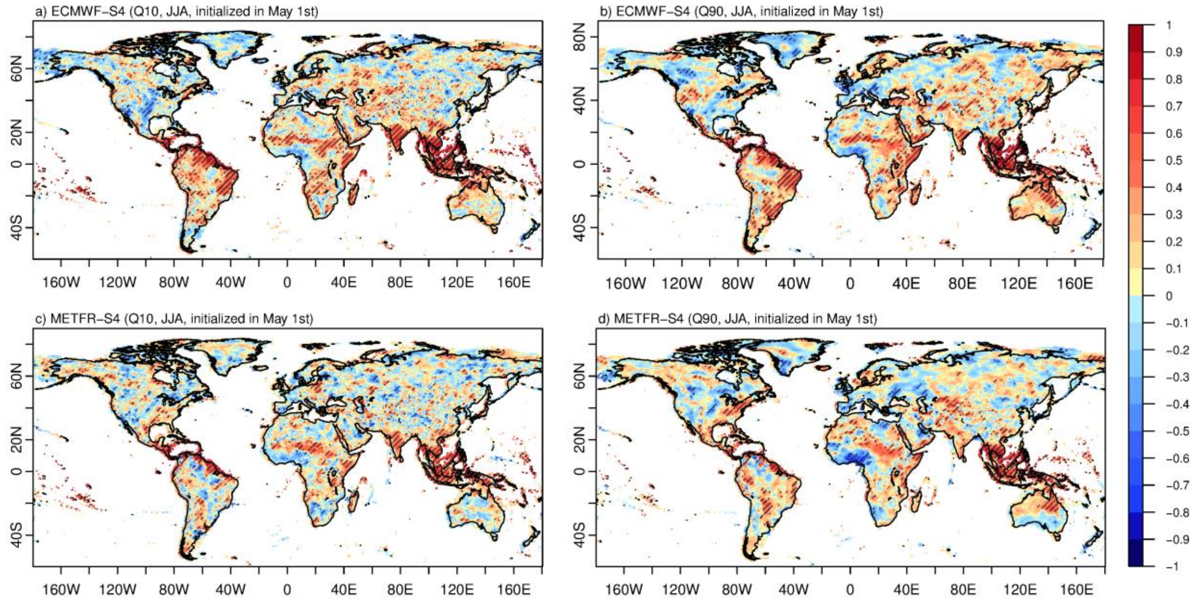

Figure 3. *Same as Fig. 2, but for summer (JJA)*

3.1.2. Fair Ranked Probability Skill Score

The DJF extreme wind events of Q10 (Figure 4a) in ECMWF-S4 show significant positive FRPSS values over the central United States, northern South America, northern China, eastern Africa and some parts of the maritime continent Generally, the significant positive skill distribution of METFR-S4 decreases compared to ECMWF-S4 in both percentiles (Figure 4c and Figure 4d). In METFR-S4 we find negative skill scores over large areas. The positively significant skill in the lower percentile of METFR-S4 can be seen in the central United States, northern South America, western Russia and some parts of Indonesia (Figure 4c). Though the skill distribution of seasonal extreme forecasts below the Q10 threshold is generally similar to that above the Q90 threshold, it can be discerned that the extreme wind speed of Q90 of Figure 4b and Figure 4d shows a much better performance than Q10 of Figure 4a and Figure 4c.

The significant FRPSS of seasonal extreme wind events in ECMWF-S4 of Figure 5b has similar patterns to the extreme prediction skill of Figure 5a, except for a slight difference over the western United States, western South America, Indian subcontinent and northern Australia. The significant high skill of the JJA extreme events of Q10 (Figure 5c) for 10m wind speed in METFR-S4 are almost indistinguishable from those of Q90 (Figure 5d), excluding some regions, such as central Asia, Indian subcontinent and northern Australia.

The differences in the skill of extreme events between the ECMWF-S4 (Figure 5 and Figure 5) and METFR-S4 (Figure 5c and Figure 5d) in each percentile are clearly shown in South America. The DJF extreme wind events for both percentiles of Figure 4 show much better skills compared to JJA extreme events of Figure 5 in almost every region, except for central Africa and the maritime continent.

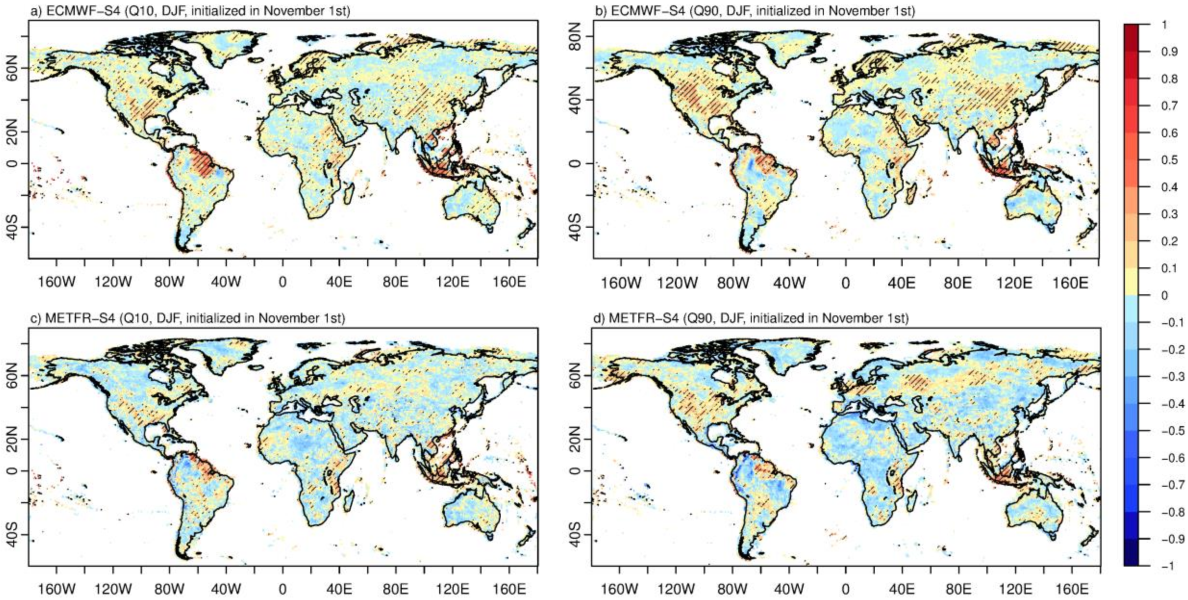

***Figure 4**. Fair Ranked Probability Skill Score for extreme 10m wind speeds*

Fair Ranked Probability Skill Score (FRPSS) of (a and b) ECMWF-S4 and (c and d) METFR-S4 with respect to the observed climatology as the reference for extreme 10m wind speeds over the globe during winter (DJF as the 3-month-average at 1-month lead initialized in November 1st) for the period 1991-2012. Left and right columns are the seasonal mean of extreme values for the 10th (Q10, a and c) and 90th percentile (Q90, b and d) threshold calculated from the 6-hourly 10m wind speeds within a given month. The hatched areas depict the regions where the FRPSS is significant at the 95% confidence level from a one-tailed Z-test.

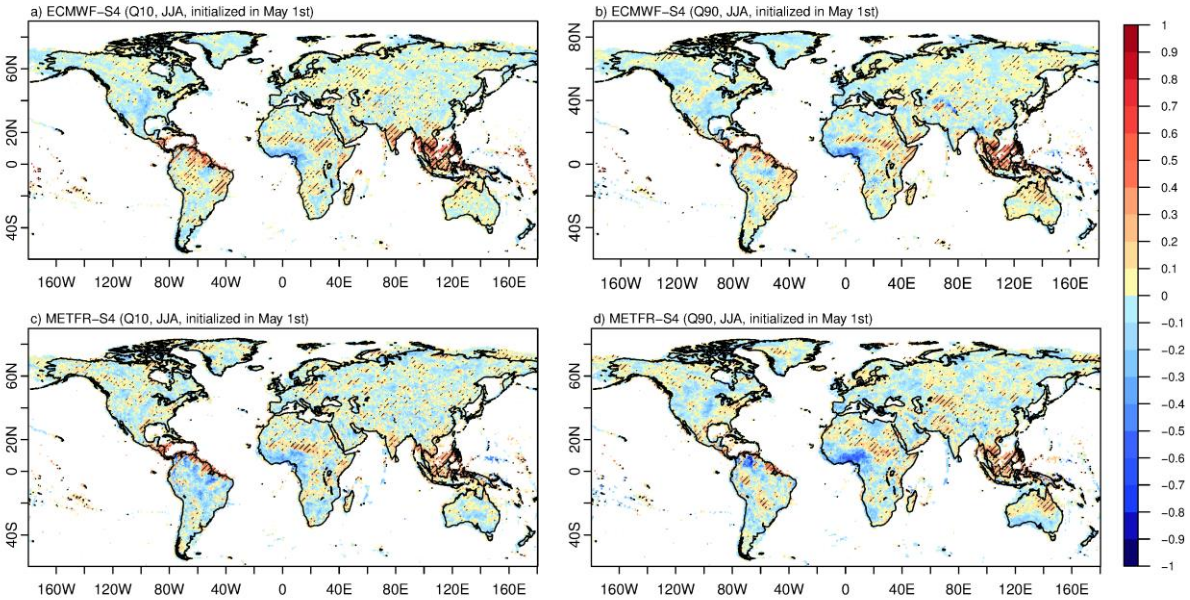

Figure 5. *Same as Fig. 4, but for summer (JJA)*

3.2. Skill of seasonal extreme forecasts with lead times

In Figure 6 and Figure 7, we have organized the time evolution of regional mean skill for the seasonal mean extreme wind forecasts as a function of lead time from 0 to 4 months. Our objective is to analyze the impacts of the lead time on the seasonal forecast skill of extreme 6-hourly 10m wind speeds for each given month. The lead time dependence of forecast skill in both ECMWF-S4 and METFR-S4 predictions is quantified by using the TCC and FRPSS as deterministic and probabilistic verification measures. Two target regions, namely Europe (15°W-45°E, 35°N-75°N) and North America (30°W-60°W, 30°N-50°N), are selected. Each season is used to examine the time variation of the performance of seasonal forecast of extreme events with the lead time (from 0 to 4 months, starting from November and May initial conditions).

In general, the area-averaged skill of seasonal extreme predictions for each Q10 and Q90 threshold from ECMWF-S4 forecast system is much better compared to METFR-S4 forecast system over both regions (Figure 6). This can be observed, especially, in the November start dates. The variability of seasonal extreme prediction skills with lead time of 0-4 months in TCC is very similar to that in FRPSS under the same initial conditions within the same region (Figure 6 and Figure 7). As expected from the impact of the initial conditions and the persistence of the seasonal predictions, the area averages of seasonal extreme prediction skill for both start dates in ECMWF-S4 forecast system are largest for the 0-month lead, and decline thereafter (except over North America). However, the decaying changes of skill in METFR-S4 forecast system are not linear(Figure 6 and Figure 7).

The seasonal extreme prediction skills of wind speed for both percentiles of ECMWF-S4 experience the sharpest decline, excluding the area-averaged skills of TCC and FRPSS over North America initialized from November 1st, between lead times of 0 and 1-month in Figure 6 and Figure 7. Furthermore, it can be seen that such a behavior of temporal correlation for wind speed is much more definitely apparent as compared to the FRPSS for the 0 and 1-month lead predictions. This means that the rate of skill decay in area-averaged TCC for wind speed is faster than in area-averaged FRPSS.

Over North America, the time evolution of the deterministic and probabilistic forecast skill in terms of the seasonal extreme wind of Q10 and Q90 in ECMWF-S4 prediction system displays a slightly increase (using the November start date in Figure 6c and Figure 6d), with some irregularities (using the May start date in Figure 7c and Figure 7d) and fluctuations. To explain these results, we propose two hypothesis. The first one is that there could be a shock that produces a systematic error as a model mean bias leading to degraded seasonal forecast skill. The other is that there is a difference between observation and prediction in terms of the trend of the wind. Even though we need to investigate this issue to provide wind energy sector with better solution, a detailed diagnosis of this issue is beyond the scope of the current study and will be a topic for future work. The prediction skills of seasonal extreme wind events of Q90 threshold in ECMWF-S4 predictions tend to be higher than those of Q10

threshold (c and d in Figure 6 and Figure 7), except for SON season of 4-month lead time starting from the May initial condition in Figure 7c and Figure 7d. This could be related with the high variability in the climate circulation that appears in that particular season. However, in METFR-S4 predictions, such a performance of seasonal extreme winds for both thresholds is not clear.

In case of the extreme predictions initialized in May it is difficult to ascertain that the performance of seasonal mean prediction of the extreme wind events for each threshold in ECMWF-S4 prediction system is superior to that in METFR-S4 prediction system (Figure 7). Over Europe (Figure 7a and Figure 7b), the seasonal predictions of extreme wind events of Q10 threshold in each prediction system tend to show higher skill than those of Q90 threshold, except in MJJ season at the lead time of 0-month.

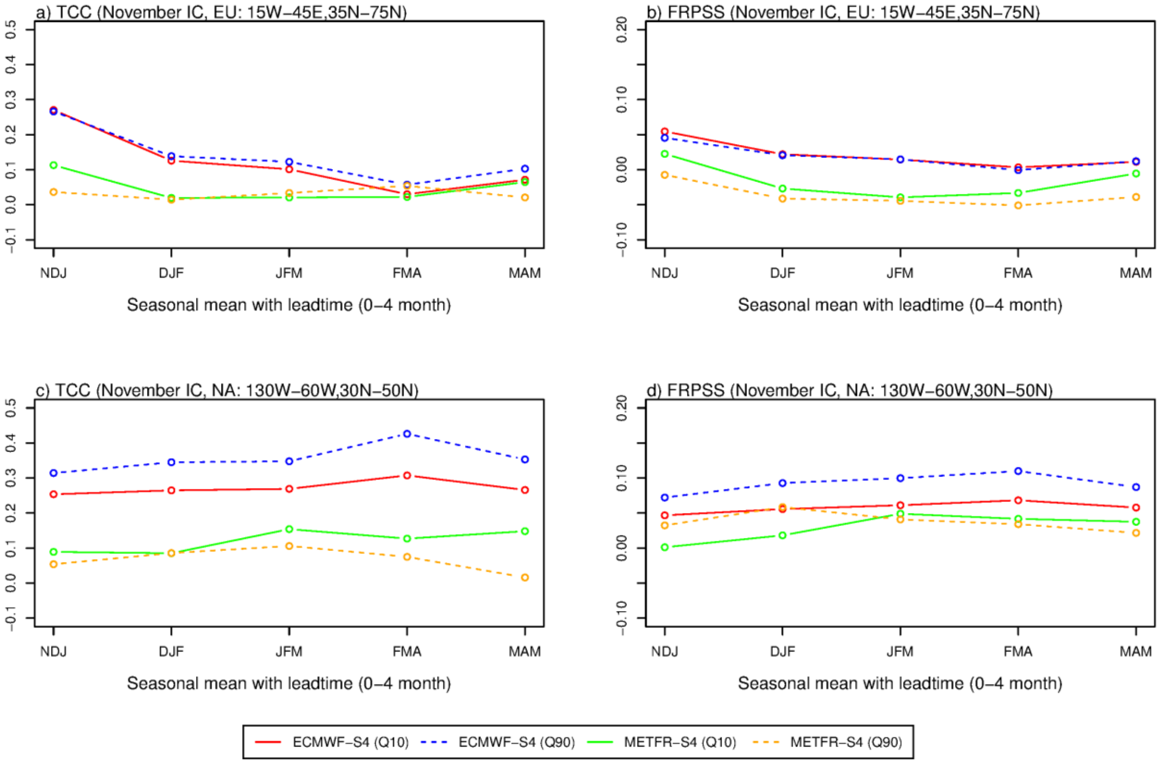

Figure 6. *Area average of TCCs and FRPSSs for predicted extreme 10m wind speed starting in November*

Area average of (a and c) TCC and (b and d) FRPSS in two prediction systems (ECMWF-S4 and METFR-S4) against observation (ERA-Interim) for seasonal extreme 10m wind speed with 0-4 month lead times initialized in November over the Europe (15°W-45°E, 35°N-75°N, a and b) and North America (130°W-60°W, 30°N-50°N, c and d) during the period of 1991-2012. Extreme events are values for the 10th (Q10) and 90th (Q90) percentile extremes.

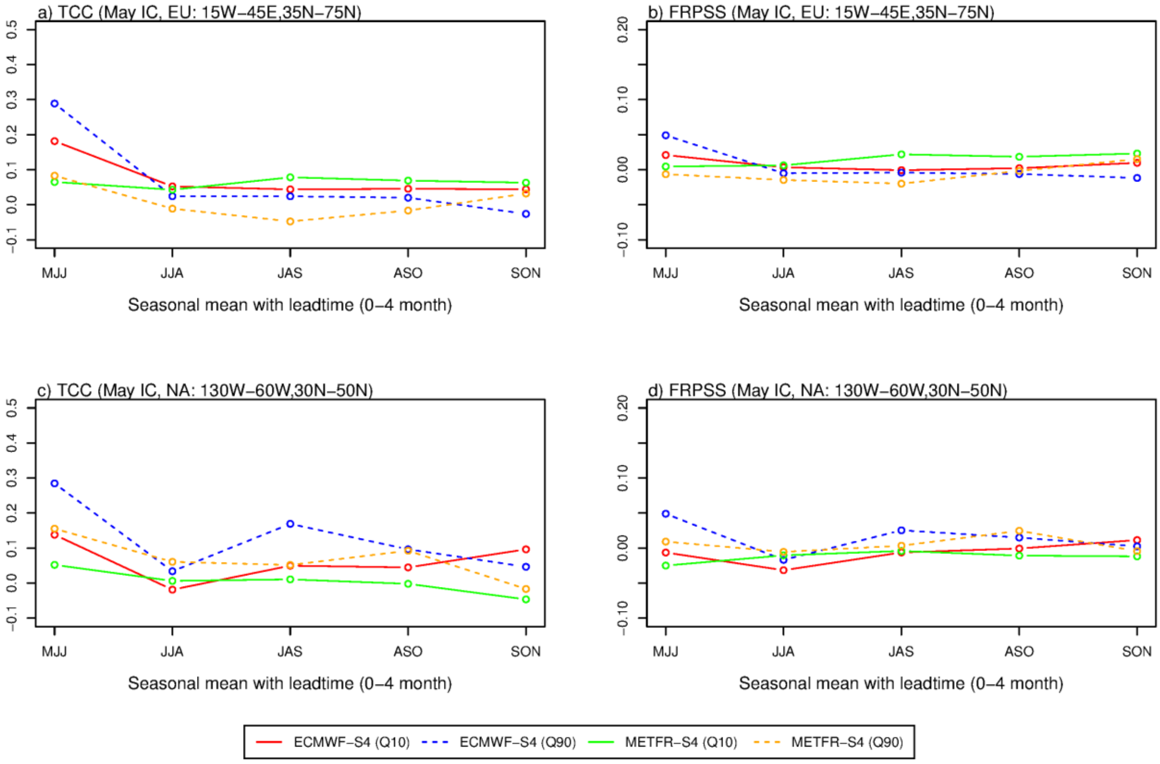

Figure 7. *Same as Fig. 6, but for initialized in May.*

4. Conclusions

In this study, we have evaluated the forecast ability of two global seasonal climate prediction systems (ECMWF-S4 and METFR-S4) in foreseeing extreme climate wind speed, aiming to minimize the risk of unexpected energy network unbalance and to provide more accurate information on the distribution/probability of occurrence for extreme wind events for the wind energy sector. To this end, we have performed the assessment using the deterministic and probabilistic skill measure, such as the TCC and RPSS, respectively.

Results show that the extreme forecast skill of the ECMWF-S4 is significantly superior to that of METFR-S4 over the whole global region during both seasons, even though the METFR-S4 forecasts show slightly better skill in a few areas, particularly such as the middle Europe, western and eastern Russia in Q90 for DJF, and some parts of the central Asia in Q90 for JJA. Moreover, in the extra-tropical (tropical) regions, the seasonal extreme wind speeds of the Q10 and Q90 in two prediction systems during DJF initialized in the first day of November display slightly better (lower) performance, as compared to those of during JJA initialized in the first day of May.

Generally, the significant spatial distributions of the FRPSS for the seasonal extreme wind events for each prediction system are very similar to those of the TCC during both seasons, although the significantly positive skill of extreme seasonal winds from ECMWF-S4 is more widespread than METFRP-S4. DJF extreme wind events based on both percentile thresholds tend to show much better skill in almost every region, except over some parts of tropical regions, as compared to the corresponding distribution for JJA.

To analyze the impact of the lead time in the skill of the seasonal extreme wind speed forecast, we have examined the time evolution of area-averaged skill for the seasonal mean extreme wind forecasts with the monthly lead time horizon. Most of the skill for seasonal extreme wind events in both thresholds indicates the highest values at the 0-month lead followed by an evident decline from lead time of 1-month and onwards. These features, for the two start dates considered (May and November), are distinctly clear in ECMWF-S4 over Europe. However, in case of seasonal extreme forecasts in METFR-S4, it is difficult to find such skill behavior. Moreover, over North America, the time evolution of the skill with lead time for seasonal extreme event in both prediction systems tends to increase slightly with the lead time, instead of decreasing, for both percentile thresholds. We briefly mentioned two possible reasons in terms of skill increase with lead time, such as a systematic error and difference of trend between observed and predicted extreme wind speed. This issue is beyond the scope of this study, and we will leave this task for future work.

This forecast quality assessment of seasonal extreme wind events shows the possibility of getting helpful climate information to prepare unexpected energy unbalance that can be caused by extreme wind speeds in wind energy industry. Nevertheless, the conclusions of this study should be taken with caution because we have used a rather small sample (hindcast period is only 22 years long) in terms of characterizing extreme wind events from simulations. In a future study, it is also necessary to provide more detailed and accurate extreme climate

information through a wider diversity of verification measures for more various regions associated with the seasonal extreme wind events. More detailed information for other seasons and variables can be found in the catalogue web site (www.bsc.es/ESS/catalogue).

5. Acknowledgements

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